Journal of Management Science and Engineering 10 (2025) 414–433

Contents lists available at ScienceDirect

Journal of Management Science and Engineering

journal homepage: www.keaipublishing.com/en/journals/journal-of-management-science-and-engineering/

Systemic financial risk analysis of the U.S. based on the complex network

Yujiao Qiu [a,b], Xiaolei Sun [c,d], Xiong Xiong [e,f], Shubin Si [a,b,*]

[a] School of Mechanical Engineering, Northwestern Polytechnical University, Xi'an, 710072, China
[b] Key Laboratory of Industrial Engineering and Intelligent Manufacturing (Ministry of Industry and Information Technology), Xi'an, 710072, China
[c] Institutes of Science and Development, Chinese Academy of Sciences, Beijing, 100190, China
[d] University of Chinese Academy of Sciences, Beijing, 100049, China
[e] College of Management and Economics, Tianjin University, Tianjin, 300072, China
[f] Laboratory of Computation and Analytics of Complex Management Systems (CACMS), Tianjin, 300072, China

ARTICLE INFO

Article history:
Received 25 August 2024
Received in revised form 26 February 2025
Accepted 7 May 2025
Available online 10 June 2025

ABSTRACT

This paper proposes a new framework for measuring systemic financial risk, which combines the Diebold and Yilmaz spillover index model, complex network, and dimensionality reduction method. This framework simulates the process of risk contagion through network dynamics, accounting for the coupled relationships between internal indicators and addressing the high-dimensional issues of financial networks. We conducted a study of the U.S. financial system from a dynamic perspective using a rolling window approach. The results reveal a strong alignment between total risk spillover and total risk contagion, and the analytical solutions and simulation results of systemic risk are consistent, which indicates the effectiveness of the measurement method for systemic financial risk proposed in this paper. Additionally, we find that hub centrality (HC) and global importance of nodes (GIN) influence the ranking algorithms' performance in identifying the nodes with the greatest influence on total systemic risk within the risk spillover networks. Furthermore, enhancing the risk resistance of a node is highly important for improving the stability and resilience of the financial system. The framework proposed in this paper provides a quantitative tool for real-time measurement of systemic financial risk and offers theoretical tools for risk managers to grasp the direction of risk management, which is crucial for the timely identification and prevention of financial crises.

© 2025 China Science Publishing & Media Ltd. Publishing Services by Elsevier B.V. on behalf of KeAi Communications Co. Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

Since the 2008 global financial crisis, systemic financial risk has attracted widespread attention from the academic community and financial regulatory authorities. However, to date, there is no universally accepted definition of systemic

* Corresponding author.
E-mail address: sisb@nwpu.edu.cn (S. Si).
Peer review under the responsibility of China Science Publishing & Media Ltd.

https://doi.org/10.1016/j.jmse.2025.05.002
2096-2320/© 2025 China Science Publishing & Media Ltd. Publishing Services by Elsevier B.V. on behalf of KeAi Communications Co. Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

risk. The contagiousness of financial risk is a widely accepted view in the theory of systemic financial risk generation. This view holds that the occurrence of systemic financial risk is due to the interdependence of economic activities among financial institutions, which can lead to the contagion of risks throughout the entire financial system when a particular institution is in jeopardy, ultimately leading to the possibility of the collapse of the total financial system, which is a global risk (Battaglia and Gallo, 2013; Allen and Gale, 2000; Kaufman, 2000; Cabrales et al., 2017). Consequently, the contagion effect is the focus of systemic risk research. In recent years, systemic financial risk has triggered multiple financial crises, dealing a significant blow to the global economy. Examples of such crises include the subprime mortgage crisis of 2008, the European sovereign debt crisis of 2009, and the COVID-19 pandemic of 2020, among others. These financial crises are often triggered by the accumulation of internal risks within the financial system, resulting in significant disruptions to the global economy and society, which attract increased attention from governments and international organizations worldwide. The U.S. financial system is one of the largest financial systems globally and has a significant impact on the development of the global financial system. The existing literature has indicated that the stability of the international financial system largely depends on the U.S. financial system (Chadwick, 2019). The systemic risk issues of the U.S. financial system could have a massive impact on the global financial system. Studying the systemic risk and risk contagion of the U.S. financial system helps identify and control risks in a timely manner from the source of risk and the process of generating risk, which is highly important for maintaining the stable and healthy development of the global financial system.

Fundamentally, the financial system is not simple, but a “complex dynamic system” composed of many interrelated elements (Leontief, 1974), and its internal structure has special characteristics such as correlation (Schweitzer et al., 2009), contagion (Allen and Gale, 2000), spillover (Welburn and Strong, 2022) and other features. Considering risk spillover effects and risk contagion is essential in the analysis of systemic risks (Lucas et al., 2018). Currently, there is no unified definition of risk spillover. The concept was first introduced by Ross (1989), who defined risk spillover from the perspective of cross-market volatility spread and argued that the flow of information between markets could lead to the spread of risk. According to relevant literature, although different scholars have varying interpretations of the risk spillover effect, it is generally believed that the risk spillover effect manifests as follows: when a risk occurs in a financial institution in the financial system, owing to the interdependence or correlation within the financial system, the risk may spread to other financial institutions and then affect the entire system, resulting in instability of the entire financial system (Battiston et al., 2016). The term “contagion” initially originated from epidemic models and was gradually applied to the financial domain. Currently, there is no consensus in the academic community regarding the definition of financial risk contagion. Among the various definitions, the three definitions of financial risk contagion provided by the World Bank have been widely cited (Caramazza et al., 2000; Billio and Pelizzon, 2003): a broad definition, a restrictive definition and a very restrictive definition. The broad definition of risk contagion refers to the phenomenon where fluctuations in one market trigger fluctuations in other markets; the restrictive definition of risk contagion refers to the correlation between financial markets that exceeds the correlation of the fundamentals of the markets with each other or the interconnection between markets in normal times. From a very restrictive perspective, only the enhanced cross-country correlations during financial crises are considered risk contagion. In this study, we adopt a broad definition, defining risk contagion as the spread of risk spillover. Accurately identifying and measuring the spillover effects of the financial system can help regulatory authorities gain a better understanding of the contagion paths of risks (Gong et al., 2023b), enabling them to take corresponding measures to mitigate the risk contagion. Additionally, it provides a more accurate measurement of the level of systemic risk by simulating risk contagion, helping financial regulatory authorities and policymakers to better understand the status of the financial system. This can enable them to assess the effectiveness of policies, adjust policy directions, and better maintain the stability of the financial system.

With the rapid development of financial globalization, the complexity of the financial system has far exceeded the situation described in traditional financial theory (Farmer and Foley, 2009). Complexity theory plays a key role in the study of risk contagion (Battiston et al., 2016), systemic risk (Haas et al., 2022) and risk management (Ma et al., 2023; Wang et al., 2024). The importance of complex networks in studying systemic financial risk has gained increasing attention (Elliott et al., 2014; Acemoglu et al., 2015; Bardoscia et al., 2021). It offers a more comprehensive and accurate analysis of risk contagion effects from the perspective of network structure. Moreover, it helps identify the nodes and pathways that significantly impact systemic risk, providing regulators with theoretical insights to manage systemic risk more effectively. Consequently, using complex network methods to explore the sources of systemic financial risk and identify systemically important nodes is becoming an increasingly key focus of research in the field of financial risk. Complex network dynamics models are based on the attributes of nodes and the topological structure characteristics of the network, considering the state transitions of nodes while exploring the network topology features, aiming to simulate the interaction mechanism between nodes during the propagation process. Therefore, from the perspective of complex network dynamics, it allows considering the cascading effects of risk propagation and analyzing the evolutionary patterns of network nodes.

However, owing to the multidimensionality of complex networks, it is difficult to deduce the properties of the entire system from the analysis of each node. Gao et al. (2016) proposed a resilience theoretical framework for separating the topology and dynamics of networks. Essentially, this framework provides a method for the equivalence and dimensionality reduction of networks, solving the “dimensional catastrophe” problem caused by the complexity of network structures. They simplified the original high-dimensional network's complex dynamical equation into a one-dimensional equivalent dynamic equation that contains only a variable parameter reflecting the network structure and an unknown variable reflecting the overall state of nodes. In fact, many complex systems in reality can be described by complex networks;

therefore, they have been widely applied in various fields. These include ecosystems (Duan et al., 2022), clinical medicine (Hou et al., 2024), and the life sciences (Si et al., 2023). Applying complex network and dimensionality reduction methods to the risk spillover network of the financial system has three main advantages. First, it enables the simulation of the risk contagion process in the financial system through dynamic experiments, allowing us to measure the systemic risk of each node in the risk spillover network. Second, it helps to solve the high-dimensional problem of financial networks by reducing the dimensionality of multi-node risk spillover networks, allowing for the quantification of the level of total risk contagion and total systemic risk. Notably, this method calculates the total systemic risk by assigning weights to each node on the basis of its risk contagion. Compared with the existing measurement methods, this approach's weighting method possesses a more explicit economic rationale and better captures the characteristics of “systemic” financial stress as distinct from localized financial stress. Additionally, it provides time-varying weights. Third, by simulating interventions, we can identify nodes that significantly impact the total systemic risk, thereby providing a scientific basis for risk management and decision-making.

In view of this, this paper proposes a framework to measure systemic financial risk based on risk cascade contagion by combining the Diebold and Yilmaz spillover index model with the dimensionality reduction method of the network while comparing analytical and numerical solutions to verify the applicability of the methodology and further study how to identify nodes that have a significant impact on overall systemic risk.

The main innovative contributions of this study include the following aspects: (1) First, the framework proposed in this paper enriches the existing research perspective by examining systemic risk within the financial system from the perspective of simulating risk contagion. This framework accounts for the coupled relationship between internal indicators and measures not only the total systemic risk but also the systemic risk across various dimensions, which is helpful for financial regulatory agencies to better understand the status of the total financial system and its various submarkets. (2) The framework proposed in this paper measures the level of systemic risk and the direction and intensity of risk contagion within the financial system simultaneously, which can assist financial regulatory institutions in understanding the direction of risk management and implementing targeted regulation. (3) Based on the risk contagion simulation results, this paper conducts a comparative analysis of various influence ranking algorithms to evaluate their effectiveness in identifying nodes with significant impacts on total systemic risk. This provides theoretical references for risk managers to identify key nodes that influence systemic risk, helping them develop more targeted risk prevention and intervention strategies to effectively control systemic risk.

The rest of the paper is organized as follows: Section 2 provides a review of the relevant literature. Section 3 details the data used in this paper and introduces the construction method of the risk spillover network, as well as the methods for measuring risk contagion and systemic risk. It also outlines how to identify nodes that have a significant impact on total systemic risk. Section 4 reports the results of empirical research based on the U.S. financial system. Section 5 concludes the paper.

2. Literature review

There are three primary methods for measuring systemic financial risk. The first is probability models or signal models, the second is composite index methods, and the third is model-based measurement methods.

The first includes the FR probability model (Frankel and Rose, 1996), the STV early warning model (Sachs et al., 1996), and the KLR signal model (Kaminsky et al., 1998), which explore and identify the common signal indicators and their threshold values for warning of crises based on the economic situation of countries that have experienced financial crises throughout history. These methods apply only to financial systems or economies that have experienced financial crises in the past or have a clear definition of systemic financial risk warning events; thus, their application is greatly limited.

The second category includes composite index methods, such as constructing a financial stress index (Illing and Liu, 2006; Ishrakieh et al., 2020) and a financial stability index (Uhde and Heimeshoff, 2009; Babar et al., 2019). These methods synthesize various relevant indicators that influence systemic financial risk, reflecting the overall condition of the financial system. They are clear, flexible and easy to use. When selecting indicators, only those that can influence systemic financial risk are considered, regardless of whether the country has experienced a financial crisis or the degree of marketization. Therefore, these methods have been widely used. However, they are challenging to use for identifying risk sources and contagion mechanisms, as they involve certain subjectivity in indicator selection, weight setting, and threshold setting, which also have limitations (Benoit et al., 2017).

The third is model-based measurement methods, which mainly measure systemic financial risk based on return loss or financial market correlations. The measurement methods based on return loss establish the importance of individual financial institutions and their spillover effects or allocate known systemic risk among various financial institutions to evaluate systemic financial risk; these methods include the CoVaR model (Tobias and Brunnermeier, 2016; Xu et al., 2019), the MES (marginal expected shortfall) (Acharya et al., 2017), the SRISK (Brownlees and Engle, 2017), and the SES (systemic expected shortfall) model (Sedunov, 2016; Acharya et al., 2017). Measurement methods based on financial market correlation evaluate systemic risk by measuring the degree of correlation among financial markets, mainly including the dynamic correlation method (Engle, 2002) and the copula method (Horta et al., 2010; Ouyang et al., 2022). Compared to the two methods mentioned above, these methods consider the complex relationships among financial institutions; however, they

primarily conduct risk measurement at the level of individual financial institutions without fully incorporating macroeconomic factors that could also influence systemic risk.

It is worth noting that the three types of risk measures mentioned above focus on the overall measurement of financial risk, which makes it difficult to reflect the intricate mechanisms of risk contagion and diffusion. Thus, an increasing number of scholars have combined traditional econometric methods with network analysis, using complex network-related knowledge to study the financial system as a complex system. Currently, network research on systemic risk can be broadly categorized into two main areas. The first category primarily analyses the characteristics of risk contagion and the impact of network structure on systemic risk from the perspective of network topology. For example, Sun et al. (2020) built a spillover network based on Diebold and Yilmaz's spillover index method and then analysed the complex interactions within the system of sovereign CDS (credit default swaps), stock and commodity markets. Gong et al. (2023a) constructed a two-layer international crude oil-geopolitical risk connectedness network based on the tail risk spillover effect among the international energy market and then revealed the interactive effects between fluctuations in international crude oil prices and geopolitical events. They also used the topology indicator values of the network as input indicators for machine learning to study the early warning impact of the link between crude oil and geopolitical factors on crude oil tail risk. Wang et al. (2022) constructed a tail-event driven network (TENET), introduced several connectivity metrics, and then explored the connectedness and systemic risk within the banking sector along the Belt and Road. Li and Wang (2021) explored how portfolio diversification affects banking systemic risk, considering three interbank network structures: random networks, small-world networks, and scale-free networks. The second category analyses the process of risk contagion from the perspective of dynamics. However, owing to the complexity of financial risk contagion paths, as well as the dynamic nature and cascading effects of the contagion process, coupled with the fact that the theory of financial risk contagion is not yet fully developed, which makes the understanding of the risk contagion mechanism is still inconclusive. The real dynamics of risk contagion in financial systems have not yet been fully understood. The existing studies have mainly used epidemic models (Garas et al., 2010; Bucci et al., 2019) and cascade failure models (Wang et al., 2022a, 2022b) to simulate risk contagion; however, in traditional epidemic models, there are states such as the susceptible state (S), infected state (I) and removed state (R) for nodes, and in cascade failure dynamics, there are active states and inactive states for nodes. This discrete classification method can indeed facilitate many studies. However, in the network of financial risk contagion, it is necessary not only to reflect whether a node is affected by other markets, but also to consider the degree of such influence. This is because the risk of nodes is usually continuously changing, and continuous contagion effects are more in line with reality. Therefore, in research, it is necessary to construct network dynamics models that are closer to reality and study the propagation laws and risk control strategies in the network, which is highly important for maintaining the stable development of the financial system.

According to the literature, analyzing financial systems via complex network theory has gradually become the mainstream trend in financial system research. However, existing research has focused on topological indicators and structural characteristics of complex networks, with relatively few studies examining the risk contagion process through dynamic approaches. Moreover, existing methods are typically aimed at discrete processes, so the research has primarily focused on comparing the positions or roles of different submarkets in the contagion of risk, but cannot further measure indices that reflect the total systemic financial risk based on the cascading effects of risk propagation. Additionally, the purpose of measuring systemic risk is to detect risks promptly so that policies can be adopted quickly to address risks and prevent crises. However, the existing literature lacks thorough research on systemic risk measurement from this fundamental goal. Consequently, this paper proposes a framework for measuring systemic risk based on risk cascade contagion while also studying how to identify the nodes that significantly influence total systemic risk. Compared with current methods, the method proposed in this research for measuring systemic financial risk considers the impact of network structure on the evolution of risk at each node, achieves dynamic simulation of financial risk propagation, and measures the level of systemic risk and the direction and level of risk contagion simultaneously.

3. Data and methodology

3.1. Data

The indicators used to assess systemic risk in the financial system should comprehensively reflect various aspects of the financial system and provide a true and real-time reflection of its systemic risk profile. The indicators used in the existing literature to reflect the overall condition of the financial system focus primarily on economic fundamentals and traditional financial markets, such as the stock market, bond market, foreign exchange market, credit derivative market, money market, and macroeconomy. Given the growing interconnection between the real economy and finance, vulnerabilities in the real economy can spread to the financial system, resulting in an increase in systemic financial risk. Moreover, policies also significantly influence systemic risk (Louis and Balli, 2013; O'Brien and Szerszeń, 2017). Therefore, we refer to the research of Hao et al. (2023), which combined indicators related to the real economy, policy measures, economic fundamentals, and traditional financial markets. We focus on constructing an indicator system for evaluating systemic risk in the U.S. financial system, covering the stock market, bond market, money market, credit derivative market, banking, foreign exchange market, macroeconomy, policy effects, and real economy. Most of the indicators in this paper are derived from the existing literature, while a small portion is selected as important indicators suitable for the U.S. financial system based on the current

Table 1
Indicator system.

Dimensionality	Variable	Economic interpretation	code
Stock market	VIX	Measures the overall volatility in stock prices (Hakkio and Keeton, 2009).	X_1
Bond market	The spread between 10-year AAA-rated bonds and 10-year Treasury notes	Reflects the condition of corporate default rates (Hsueh and Chandy, 1989; Cardarelli et al., 2011).	X_2
Money market	The spread between the 1-month nonfinancial commercial paper rates and 1-month Treasury bills	Reflects the market's assessment of the default risk of commercial paper.	X_3
Credit derivatives market	The spread between investment-grade corporate CDs and same-maturity Treasury notes	Reflects the systemic default and solvency conditions (Bao et al., 2011).	X_4
Banking	KWB Bank Index/Dow Jones Industrial Average Index	Reflects the risk conditions and expectations of banks.	X_5
	TED spread	Reflects the level of liquidity stress, indicating the willingness or ability for short-term interbank lending (Cardarelli et al., 2011).	X_6
	Deposit-to-asset ratio	Reflects the ability of banks to maintain stable and sustainable operations (Merton, 1977).	X_7
Foreign exchange market	US dollar index	Reflects the changes in the US dollar (Chen and Zhang, 2023).	X_8
Macroeconomics	The 10-year minus 3-month treasury yield spread	Reflects the level of macroeconomic pressure (Estrella and Hardouvelis, 1991).	X_9
	CPI	Reflects the level of inflation (Estrella and Mishkin, 1998).	X_{10}
Policy effect	The difference between the federal funds rate target and the actual rate	Reflects the actual effects of the Federal Reserve's monetary policy implementation.	X_{11}
Real economy	NFIB Small Business Optimism Index	Reflects the confidence of small business owners in economic development (Anglin et al., 2018).	X_{12}
	Increase in nonfarm payrolls	The main indicator that reflects employment conditions.	X_{13}
	Sentix Investor Confidence Index	Measures the level of investor confidence in economic activity.	X_{14}
	PMI	Reflects the overall growth or decline in the manufacturing or service industries (Erik et al., 2019).	X_{15}

state of systemic financial risk in the U.S. and the principles of data availability and objectivity. The specific indicators are shown in Table 1.

To study the trends of systemic financial risk in the U.S. as comprehensively as possible across different periods, while also considering data availability, we collected data for 15 indicators from the WIND database from January 2003 to April 2024. The sample covers multiple major economic events, including the subprime mortgage crisis and the COVID-19 pandemic; thus, the data can fully reflect the fluctuations in systemic risk during different periods. As there are differences in the frequency of the data, we use the arithmetic mean method to convert daily and weekly data to monthly data. We apply first-order differencing to meet the VAR model's needs and present the descriptive statistics in Table A.1.

3.2. Methodology

3.2.1. Diebold and Yilmaz spillover index model

Diebold and Yilmaz (2012) proposed a method that uses generalized forecast error variance decomposition to extract the spillover index. This method not only measures the intensity of risk spillovers but also provides information on the direction of risk transmission.

For a covariance stationary VAR model with N variables and a lag of p periods:

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-i} + \varepsilon_t \tag{1}$$

where $x_t = (x_{1t}, x_{2t}, \ldots, x_{Nt})$ represents the n-dimensional endogenous variables, $\varphi_i, i = 1, 2, \ldots, p$ represents the $N \times N$ coefficient matrices to be estimated, $\varepsilon_t \sim (0, \Sigma)$ represents the N-dimensional perturbation column vector with independent and identically distributed components, and Σ represents the covariance matrix.

Assuming that the covariance of the VAR model is stable, through a moving average, Eq. (1) can then be rewritten as follows:

$$x_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j} \tag{2}$$

where A_j denotes the $N \times N$ identity matrix and satisfies the expression $A_j = \phi_1 A_{j-1} + \phi_2 A_{j-2} + \ldots + \phi_p A_{j-p}$, with A_0 being an $N \times N$ identity matrix and with $A_j = 0$ for $j < 0$.

The spillover effect of variable x_j on variable x_i is defined as the variance of the H-step forecast error of x_i that is affected by the shock from x_j, reflecting the extent to which a change in a variable is determined by itself or other variables. Here, $i \neq j$, and the H-step represents the periods in the variance decomposition and is expressed in the following formula:

$$\theta_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j \right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_j \right)} \tag{3}$$

where σ_{jj} is the standard deviation of the error term ε_j and e_i is the selection vector, with a value of 1 for the ith element and 0 otherwise. θ_{ij}^{H} explains the shocks contributed by the financial variable x_j to the variance of the forecast error of another variable x_i. However, since $\sum_{j=1}^{N} \theta_{ij}^{H} \neq 1$, θ_{ij}^{H} needs to be normalized as follows:

$$\tilde{\theta}_{ij}^{H} = \frac{\theta_{ij}^{H}}{\sum_{j=1}^{N} \theta_{ij}^{H}} \tag{4}$$

The matrix $\tilde{\theta}^{H} = [\tilde{\theta}_{ij}^{H}]$ describes the spillover effects among the N variables, where $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{H} = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{H} = N$.

The total risk spillover index incorporates pairwise effects and reveals the level of system-wide risk contagion in the form of volatility spillovers. The percentage form of the total risk spillover index (TRS) is as follows:

$$TRS = \frac{\sum_{i,j=1, i \neq j}^{N} \widehat{\theta}_{ij}^{H}}{\sum_{i,j=1}^{N} \widehat{\theta}_{ij}^{H}} \times 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \widehat{\theta}_{ij}^{H}}{N} \times 100 \tag{5}$$

The directional spillover index measures the risk spillover effect between a specific indicator and all other indicators. The spillovers from indicator i to the remaining indicators, that is, “to others”, are given by:

$$S_{\cdot i} = \sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ji}^{H} \times 100 \tag{6}$$

The spillover index to indicator i arises from the remaining indicators, that is, “from others”, given by:

$$S_{i \cdot} = \sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ij}^{H} \times 100 \tag{7}$$

The net spillover index (NS) of a certain indicator i is defined as the difference between the spillover to all others and the spillover from others, which is written as follows:

$$NS_i = S_{\cdot i} - S_{i \cdot} \tag{8}$$

3.2.2. Construction of risk spillover networks

The intricate risk spillover within the financial system creates the risk spillover network. Based on the theory of complex networks, we consider the indicators in Table 1, which reflect the risk conditions of the financial system, as nodes in the risk spillover network. The risk spillover relationships between these indicators are represented as edges connecting the nodes, thereby constructing the risk spillover network for the financial system. The network constructed by this method is weighted and directed, and is more realistic and convenient for analysing the characteristics and evolution of the risk spillover networks in different sample periods. To study the time-varying characteristics of the U.S. financial system, we employ the sliding window technique. To achieve a smooth representation of the index while avoiding information distortion, we set the window size to 36 and the moving step size to 1, resulting in 220 networks. The detailed construction process of the dynamic risk spillover network is shown in Fig. 1.

3.2.3. Dynamic model of risk contagion

Network dynamics describes how networks transmit certain forms of matter, energy, or information. For example, gene regulatory dynamics (Karlebach and Shamir, 2008) can reflect the regulatory mechanisms of gene expression in organisms, epidemic models (Dodds and Watts, 2005) can reflect the spread of diseases and rumors, and pairwise comparisons with the Fermi function (Traulsen et al., 2006) can reflect decision-making processes, strategy updates, or behavioural changes based on mutual comparisons among individuals. Considering a complex network system with N nodes, the basic form of the dynamical equations can be represented by a differential equation of the following form (Barzel and Barabási, 2013):

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = F(x_i) + \sum_{j=1}^{N} A_{ij} G\left(x_i, x_j\right) \tag{9}$$

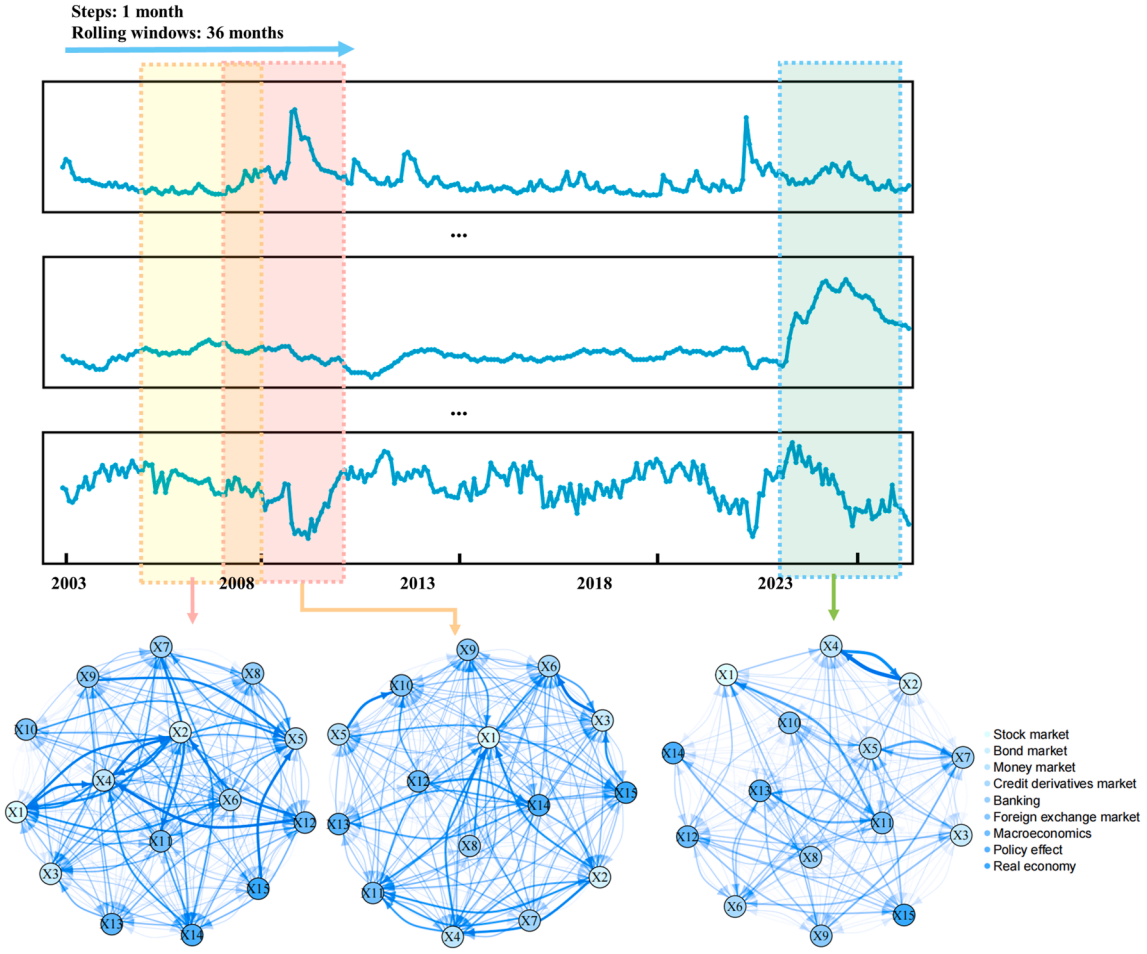

Fig. 1. Schematic diagram of the risk spillover network construction.

where x_i represents the activity of node i at time t, A_{ij} describes the internal dynamics of node i, and $\sum_{j=1}^{N} A_{ij} G(x_i, x_j)$ describes the interaction dynamics between neighbouring nodes and node i. The weighted adjacency matrix A_{ij} quantifies the interactions between nodes in the system. By appropriately selecting A_{ij} and $G(x_i, x_j)$, Eq. (9) can be used to simulate many complex systems in the real world.

In this study, we assume that risk is an inherent attribute of nodes within the range $[0, 1]$ rather than being acquired through activation. Additionally, for node i, even if its neighbouring nodes have relatively low risk levels and risk contagion strengths, they can still transmit risk through the network to node i, thereby increasing its systemic risk. Therefore, we choose the birth–death process (Novozhilov et al., 2006) to study the contagion of risk within the financial system. The birth–death process is a special type of stochastic process, which is a Markov chain with transitions occurring only between adjacent states. Its adjacent transition mechanism corresponds to the characteristics of systemic risk fluctuations in the financial system, making it highly appropriate for modelling the dynamic process of risk contagion within the financial system. It has many applications in population dynamics, queuing theory, and biology. This process can be described by a dynamic equation in the following form:

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = -Bx_i^b + \sum_{j=1}^{N} A_{ij} R x_j^a \tag{10}$$

where x_i represents the systemic risk of the node i and A_{ij} represents the risk spillover from node j to node i, which is the level of risk contagion from node j to node i. The first term on the r.h.s. represents the risk adjustment of node i, the coefficient B denotes the ability of node i to resist risk, and the exponent b reflects the characteristics of the dynamics. Generally, b is set to 2 to denote pairwise depletion. In this paper, we set $b = 2$ to represent the risk adjustment function of institutions within the financial system. The second term describes the risk contagion to node i from node i's neighbouring node j; in the birth–death process, the interaction terms are usually linear. For example, when simulating population dynamics, the interaction term describes the population flow to node i from node i's neighbouring node j, which is usually

proportional to the population size of the adjacent nodes. We also adopt a similar simplification, assuming that the increase in risk at node i due to its neighbouring node j is proportional to the risk at node j, so we set $a = 1$. Moreover, R represents the ability of neighbouring nodes to transmit risk to node i. This dynamic equation captures the influence of the network structure and node coupling effects on risk contagion.

When the system reaches a steady state, Eq. (9) becomes the following form:

$$-B\left(x_i^*\right)^2 + \sum_{j=1}^{N} A_{ij} R x_j^* = 0 \tag{11}$$

To reduce the dimensionality of Eq. (11), we utilize the dimensionality reduction method proposed by Gao et al. (2016) to transform the high-dimensional network in Eq. (11) into a one-dimensional resilience equation that contains only two indices. One index reflects the network structure and thus essentially represents the total risk contagion of the network, which we name TRC (total risk contagion). The other index reflects the overall state of nodes and is essentially the weighted sum of the states of N nodes in the original network, with the weight proportional to the out-degree of each node, which we name TSR (total systemic risk). The one-dimensional resilience equation is as follows:

$$-B \cdot TSR^2 + R \cdot TRC \cdot TSR = 0 \tag{12}$$

where:

$$TSR = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} A_{ij} x_j}{\sum_{i=1}^{N}\sum_{j=1}^{N} A_{ij}} \tag{13}$$

$$TRC = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} A_{ij} A_{ji}}{\sum_{i=1}^{N}\sum_{j=1}^{N} A_{ij}} \tag{14}$$

Then, we can similarly obtain the systemic risk for each dimension by the dimensionality reduction approach. To distinguish it from the total systemic risk, we use the SR to represent the systemic risk for each dimension. Assuming that the dimensionality k is made up of the variable $k_1, \cdots, k_n \in [1, N]$ and that the dimensionality l is made up of the variable $l_1, \cdots, l_m \in [1, N]$, the systemic risk of dimensionality k (SR_k) and l (SR_l) can be obtained as follows:

$$SR_k = \frac{\sum_{\eta=1}^{n}\sum_{i=1}^{N} A_{ik_\eta} x_{k_\eta}}{\sum_{\eta=1}^{n}\sum_{i=1}^{N} A_{ik_\eta}} \tag{15}$$

$$SR_l = \frac{\sum_{\gamma=1}^{m}\sum_{i=1}^{N} A_{il_\gamma} x_{l_\gamma}}{\sum_{\gamma=1}^{m}\sum_{i=1}^{N} A_{il_\gamma}} \tag{16}$$

To obtain the analytical solution for systemic risk, we use the mean-field theory (Si et al., 2023; Meng et al., 2025) to transform $\sum_{j=1}^{N} A_{ij} x_j$ into $k_i \cdot TSR$, where $k_i = \sum_{j=1}^{n} A_{ij}$ and $k_i \cdot TSR$ represents the average impact that i receives from its neighbourhood, so the equation becomes:

$$-B\left(x_i^*\right)^2 + R \cdot k_i \cdot TSR = 0 \tag{17}$$

where x_i^* represents the analytical solution for the systemic risk of each node and is obtained as follows:

$$x_i^* = \sqrt{\frac{Rk_i TSR}{B}} \tag{18}$$

Furthermore, the analytical solution for the total systemic risk (TSR^*) and the systemic risk in dimensionality k (SR_k^*) and l (SR_l^*) can be obtained as follows:

$$TSR^* = \langle x_i^* \rangle = \sum_{i=1}^{N} \frac{x_i^*}{N} = \sum_{i=1}^{N} \frac{1}{N} \sqrt{\frac{Rk_i TSR}{B}} \tag{19}$$

$$SR_k^* = \langle x_{k_\eta}^* \rangle = \sum_{\eta=1}^{n} \frac{x_{k_\eta}^*}{n} = \sum_{\eta=1}^{n} \frac{1}{n} \sqrt{\frac{Rk_{k_\eta} TSR}{B}} \tag{20}$$

$$SR_l^* = \langle x_{l_\gamma}^* \rangle = \sum_{\gamma=1}^{m} \frac{x_{l_\gamma}^*}{m} = \sum_{\gamma=1}^{m} \frac{1}{m} \sqrt{\frac{Rk_{l_\gamma} TSR}{B}} \tag{21}$$

Table 2
Some influence ranking algorithm.

Algorithm	Equation	Description
PageRank (PR)	$PR_i = \alpha\sum_j A_{ij}\frac{x_j}{k_j} + \frac{1-\alpha}{N}$	PR considers both the number of links pointing to the node and the influence of the link source as key factors of the node's influence (Page et al., 1999).
Betweenness centrality (BC)	$BC_i = \frac{1}{(N-1)(N-2)}\sum_{s\neq i\neq t}\frac{\sigma_{st}(i)}{\sigma_{st}}$	BC_i represents the measure of the number of times a node acts as a bridge along the shortest path between two other nodes in a network, σ_{st} represents the number of shortest paths from node s to node t, and $\sigma_{st}(i)$ represents the number of these paths that pass through node i (Newman, 2005).
Closeness centrality (CC)	$CC_i = \frac{N-1}{\sum_{j=1}^{N} d_{ij}}$	CC_i represents how close a node is to all other nodes in a network, typically measured as the reciprocal of the sum of the shortest path distances from the node to all other nodes. d_{ij} represents the length of the shortest path from node i to node j (Freeman, 1978).
HITs Authority centrality (AC)	$AC_i = \alpha\sum_j A_{ij}HC_j$	Authoritative nodes are nodes that contain useful information on the topic, and nodes with high AC are defined as those pointed to by a large number of hub nodes (Gleich, 2015).
Hubs centrality (HC)	$HC_i = \beta\sum_j A_{ij}AC_j$	Hub nodes indicate where to find the most suitable authoritative nodes, and nodes with high HC referring to nodes that link to many nodes with high AC (Gleich, 2015).
Gravity centrality (GC)	$GC_i = \sum_{j\neq i, d_{ij}\leq\langle d\rangle/2}\frac{k_i k_j}{d_{ij}^2}$	GC incorporates both the node degree and topological distance between nodes, considering both local and global information (Ma et al., 2016).
Laplacian centrality (LC)	$E(G) = \sum_{i=1}^{n} k_i^2 + \sum_{i=1}^{n} k_i LC_i = \Delta E_i = E(G) - E(G_{-i})$	$E(G)$ represents the Laplacian energy of network, and LC_i represents the Laplacian energy loss after the removal of node i (Qi et al., 2013).
Laplacian gravity centrality (LGC)	$LGC_i = \sum_{j\neq i, d_{ij}\leq\langle d\rangle/2}^{n}\frac{LC(i)LC(j)}{d_{ij}^2}$	LGC integrates the principles of both the GC and LC algorithms, substituting the degree of nodes in the GC method with the LC of nodes (Zhang et al., 2022).
Global importance of node (GIN)	$GIN_i = e^{\frac{1}{k_i\cdot\alpha}} \times \sum_{i\neq j}\frac{k_i\cdot\beta}{d_{ij}}$	GIN is a hybrid algorithm based on local and global information. In the formula, the first represents self-importance and the second represents global importance (Zhao et al., 2020).
Local-and-global-centrality (LAGC)	$LAGC_i = \frac{k_i}{n} \times \sum_{i\neq j}\frac{\sqrt{k_j+\alpha}}{d_{ij}}$	LAGC is the combination of local local-influence and global influence. In the formula, the first represents the local influence, and the second represents the global influence (Ullah et al., 2021).

The analytical solution and simulation results of the same index have the same meaning, representing the systemic risk when risk contagion reaches stability. By comparing the analytical solution and simulation results of the same index, we can evaluate the effectiveness of the dimensionality reduction method in the risk contagion network.

3.2.4. Measurement and ranking of node influence

In the risk spillover network, different nodes have varying impacts on the total systemic risk. Therefore, it is essential to identify potential key nodes that significantly influence systemic risk, thereby better guiding the direction of risk management. Numerous algorithms have been developed to calculate and rank the influence of nodes in complex networks. Thus, we first review some algorithms, as shown in Table 2, and then introduce common evaluation metrics to assess their effectiveness.

To evaluate the performance of different node influence ranking algorithms, we compare the actual influence of nodes with the results from the algorithms and use metrics such as the coefficient of determination, the Kendall coefficient, and the imprecision function for assessment.

To visually represent the correlation between the actual influence of nodes and the results of the algorithm, we first present a scatter plot with a linear regression line. We then introduce the coefficient of determination to measure the degree of fit between the regression line and the scatter points. The formula for calculating the coefficient of determination is as follows:

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{22}$$

where y_i and $\hat{y}_i$ represent the actual and estimated values of the y-coordinate for node i, respectively, and $\bar{y}$ represents the mean of the y-coordinates for all nodes. Since the fitted regression line describes a linear correlation, a higher coefficient of determination indicates better performance of the corresponding influence ranking algorithm.

The Kendall coefficient (Kendall, 1938) is defined as the ratio of the difference between the number of concordant pairs and the number of discordant pairs to the total number of pairs. Given two ranking sequences X and Y with elements $(x_1, x_2, \cdots, x_N)$ and $(y_1, y_2, \cdots, y_N)$. For any randomly selected pairs (x_i, y_i) and (x_j, y_j), the pairs are considered concordant pairs if $x_i > x_j$ and $y_i > y_j$ or if $x_i < x_j$ and $y_i < y_j$. Otherwise, the pairs are discordant. If $x_i = x_j$ or $y_i = y_j$, the pairs are neither concordant nor discordant. The Kendall coefficient is expressed in the following form:

$$\tau(X,Y)=\frac{2(N_c-N_d)}{N(N-1)} \tag{23}$$

where N_c and N_d refer to the number of concordant and discordant pairs, respectively. Specifically, a higher Kendall coefficient indicates that the results of the influence algorithm are closer to the actual values of the node influence.

The imprecision function (Kitsak et al., 2010) assesses the accuracy of different node influence ranking algorithms in identifying key nodes by comparing the average spreading capacity of the top pN nodes ranked by the algorithm with the actual influence sequence of the nodes. The closer the value of $\varepsilon_\theta(p)$ is to 0, the more accurately the influence ranking algorithm captures the most influential nodes in the network. The imprecision function is defined as follows:

$$\varepsilon_\theta(p)=1-\frac{M_\theta(p)}{M_{eff}(p)} \tag{24}$$

where $p\in[0,1]$, $M_\theta(p)$ and $M_{eff}(p)$ denote the average spreading capacity of the top pN nodes in the node importance sequence calculated by the algorithm and the actual influence sequence, respectively.

4. Empirical analysis

4.1. Measurement of systemic risk

In this section, we use the fourth-order Runge–Kutta method for dynamic simulation and set $B=R=1$ to study the dynamic changes in the U.S. financial system.

We first obtained the dynamic changes of the values of the TRC and TRS in the U.S. financial system. The TRC is obtained through the dimensionality reduction of the network using Eq. (14), and its value reflects the level of total risk contagion of the network. Since we adopt the broad definition of risk contagion proposed by the World Bank, which defines risk contagion as the impact of risk spillover on other nodes, leading to the infection of those nodes with risk, we plot the values of the TRC and TRS together in Fig. 2, from which several observations can be made. First, the total risk spillover based on the Diebold and Yilmaz model and the total risk contagion are in good agreement, indicating that the dimensionality reduction method can effectively achieve dimensionality reduction of the risk spillover network. Second, the indices obtained by the two methods consistently remain between 0.60 and 0.95, which indicates that the degree of risk contagion in the U.S. financial system was strong. Third, from the perspective of changing trends, the indices obtained by the two methods showed significant fluctuations and were notably greater during major crisis events than during other periods. This finding indicates that major crisis events significantly exacerbated risk contagion within the financial system.

Fig. 3 shows the dynamic changes of total systemic risk. The results of the dynamic analysis of total systemic risk reveal that the sample period can be roughly divided into six stages. From January 2006 to June 2007 (Stage 1), the total systemic risk remained at a low level of fluctuation. During this stage, the U.S. economy and financial environment were relatively stable, without major financial crises or turbulent events. From June 2007 to September 2011 (Stage 2), the total systemic risk experienced significant volatility and remained at a high level of fluctuation. This stage reflected the impact of the

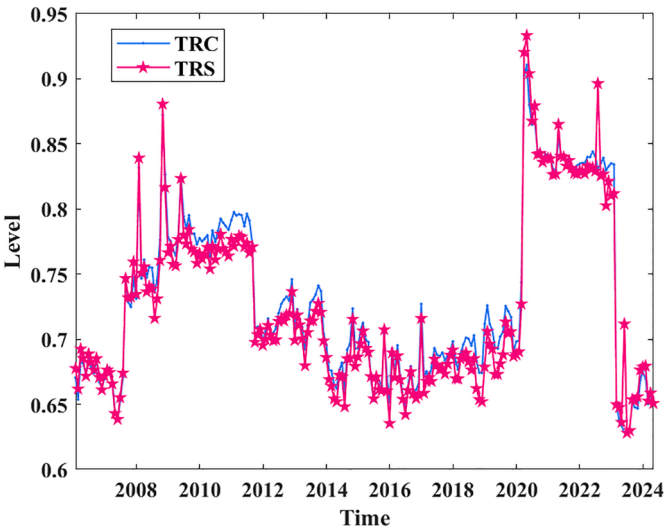

Fig. 2. The dynamic changes of TRC and TRS.

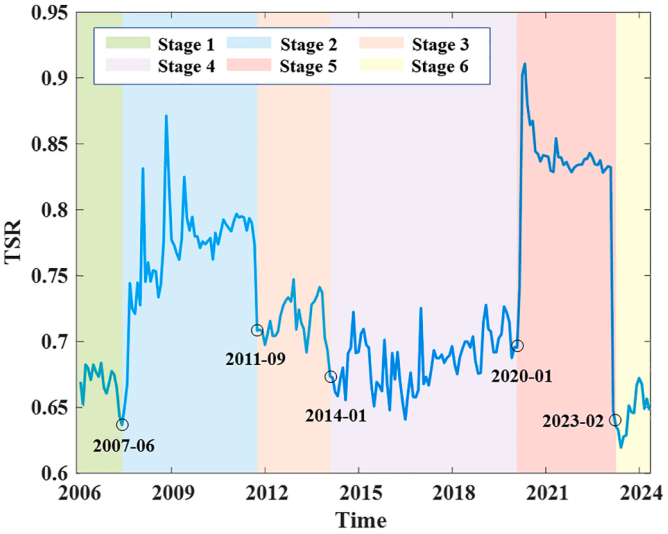

Fig. 3. The dynamic changes of the total systemic risk.

subprime mortgage crisis and the European debt crisis on the U.S. financial system. From September 2011 to January 2014 (Stage 3), the total systemic risk recovered and experienced several periodic fluctuations at a relatively high level, ranging from 0.69 to 0.80. In this stage, the U.S. financial system experienced a phase of recovery and reconstruction from the subprime mortgage crisis. On the one hand, after the start of the subprime mortgage crisis, the U.S. government implemented a number of rescue measures, which gradually yielded results. Market confidence gradually increased, and systemic risk decreased. On the other hand, the European debt crisis continued to ferment during this period. From January 2014 to January 2020 (Stage 4), the total systemic risk remained at a relatively low level, fluctuating from 0.64 to 0.71. During this period, the U.S. financial system operated relatively smoothly, and the U.S. economy showed a gradual recovery trend. For example, the unemployment rate continued to decline, and the consumer confidence index increased. However, there were also several risks, such as low inflation rates, international trade frictions, and political uncertainties. From January 2020 to February 2023 (Stage 5), the total systemic risk increased sharply to reach a peak of 0.9108 during the full sample period in April 2020, followed by a steep decline but remained at a high level of fluctuation until January 2023, when the total systemic risk began to decline continuously. This stage reflected the impact of the COVID-19 pandemic and the Russia–Ukraine conflict. In January 2020, COVID-19 emerged globally, sparking uncertainty and market volatility in the global economy. The U.S. government subsequently implemented large-scale monetary and fiscal stimulus measures, including interest rate cuts and quantitative easing, to mitigate the economic impact of the pandemic. Additionally, on February 24, 2022, the Russia–Ukraine conflict broke out, causing panic in global markets and increasing uncertainty and risk in the financial markets. From February 2023 to April 2024 (Stage 6), the total systemic risk remained fluctuating at a lower level, ranging from 0.61 to 0.68. This period reflected that the implementation of ongoing policy measures contributed to a more stable financial system.

Fig. 4 illustrates the variation in systemic risk across different dimensions. Like total systemic risk, systemic risk across various dimensions was greater during the subprime crisis period and the COVID-19 pandemic period. Moreover, the level of systemic risk during the COVID-19 pandemic was generally higher than that during the subprime mortgage crisis, indicating that the impact of COVID-19 on the U.S. financial system was greater than that during the subprime mortgage crisis. Additionally, performance across dimensions during the COVID-19 pandemic and the subprime mortgage crisis exhibited distinct characteristics. For example, during the subprime mortgage crisis, systemic risk across dimensions displayed considerable volatility. In contrast, during the COVID-19 pandemic, while systemic risk in the foreign exchange market and macroeconomy initially surged before exhibiting a general trend of fluctuating decline, the systemic risk in other dimensions surged and then experienced a temporary decrease, subsequently stabilizing at relatively higher levels. The subprime mortgage crisis originated from the housing bubble during a period of low interest rates, which essentially led to an explosion of issues within the financial system. In February 2007, the risks of mortgage loans in the U.S. began to surface, followed by the gradual spread of the subprime mortgage crisis. The bankruptcy of Lehman Brothers in September 2008 triggered a global financial crisis, followed by a series of rescue measures implemented by the U.S. government. The outbreak of the subprime mortgage crisis led to instability in global financial markets and further deterioration of debt problems in European countries. In December 2009, the three major rating agencies downgraded Greece's sovereign rating, intensifying the Greek debt crisis, which then spread to other Eurozone countries. Eventually, the European debt crisis erupted, posing the most severe challenge since its inception eleven years prior. Many U.S. financial institutions held the debt of European countries, and the European debt crisis had a significant effect on the U.S. financial system. This accounts

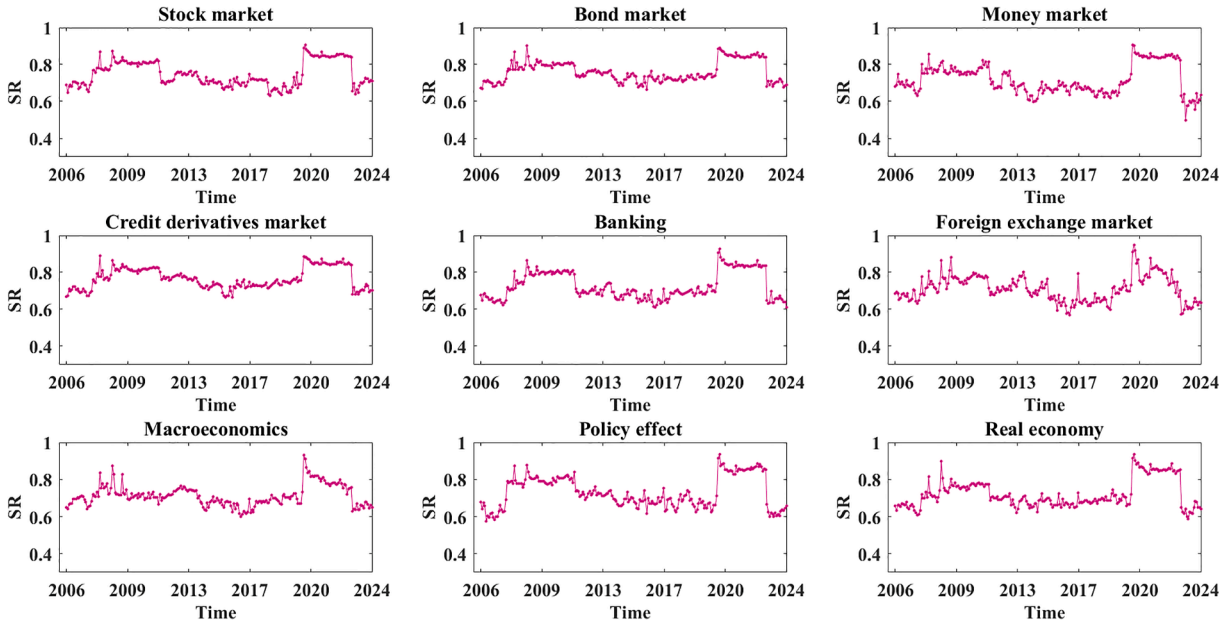

Fig. 4. The dynamic changes of the systemic risk changes across various dimensions.

for the pronounced fluctuations in systemic risk across various dimensions during the subprime mortgage crisis. However, the COVID-19 pandemic is an exogenous shock that has had a dual impact, affecting the real economy through supply chain disruption (Chowdhury et al., 2021) while also shaking investor confidence. Through the functioning of leverage and correlation mechanisms, the adverse effects of the pandemic were multiplied and propagated within the financial system, resulting in market volatility and an increase in systemic financial risk. As central banks around the world launched coordinated intervention measures, such as injecting liquidity and lowering interest rates, market confidence gradually recovered, leading to a reduction in the volatility of the foreign exchange market and a decrease in systemic risk levels. Moreover, the rapid implementation of large-scale fiscal and monetary policies, such as fiscal subsidies, relief payments, interest rate cuts, and quantitative easing, alleviated the pressure from economic decline, resulting in a decrease in macroeconomic systemic risk levels. However, the uncertainty and recurrence of the pandemic have led to systemic risks remaining at relatively high levels in other dimensions.

Furthermore, as shown in Fig. 4, systemic risks in the money market, banking market, and foreign exchange market started to exhibit a slight upward trend in March 2023, whereas risks in other dimensions began to increase only in April 2023. This result indicates that the collapse of Silicon Valley Bank had an immediate and significant effect on the money market, banking market, and foreign exchange market. Owing to the coupled relationships between various indicators within the financial system, risks in these dimensions quickly spread to other dimensions. Over the following ten months, systemic risk across various dimensions generally exhibited a slight upward trend, resulting from a confluence of multiple factors, including persistent inflationary pressures and high interest rates, the bankruptcy of Silicon Valley Bank and several other banks, and escalating geopolitical tensions. Moreover, the increase in systemic risk was reduced by timely measures to control the spread of risks including the FDIC receivership and the BTFP financing program.

We calculate the analytical solution of the systemic risk for the total financial system and each node in the risk spillover network according to Formulas (19), (20) and (21), and plot the analytical solutions and simulation results of each group together, as shown in Fig. 5, where SR represents the simulation results of each dimension, SR* represents the analytical solutions of each dimension, TSR represents the simulation results of the total systemic risk, and TSR* represents the analytical solutions of the total systemic risk. The graphical evidence shows that the analytical solutions and simulation results for systemic risk are in good agreement, indicating that the simulation results obtained by solving the high-dimensional equation are consistent with the theoretical solution derived by directly solving the one-dimensional function after dimension reduction. This further suggests that the methodology proposed in this paper is feasible for measuring systemic risk.

4.2. Influence of nodes on systemic risk

The state of the system can be changed through microscopic interventions, such as controlling just one node (Sanhedrai et al., 2022). To study the control capacity of each node over systemic risk, we force node i to follow $x_i(t) = fx_i^*$. During the

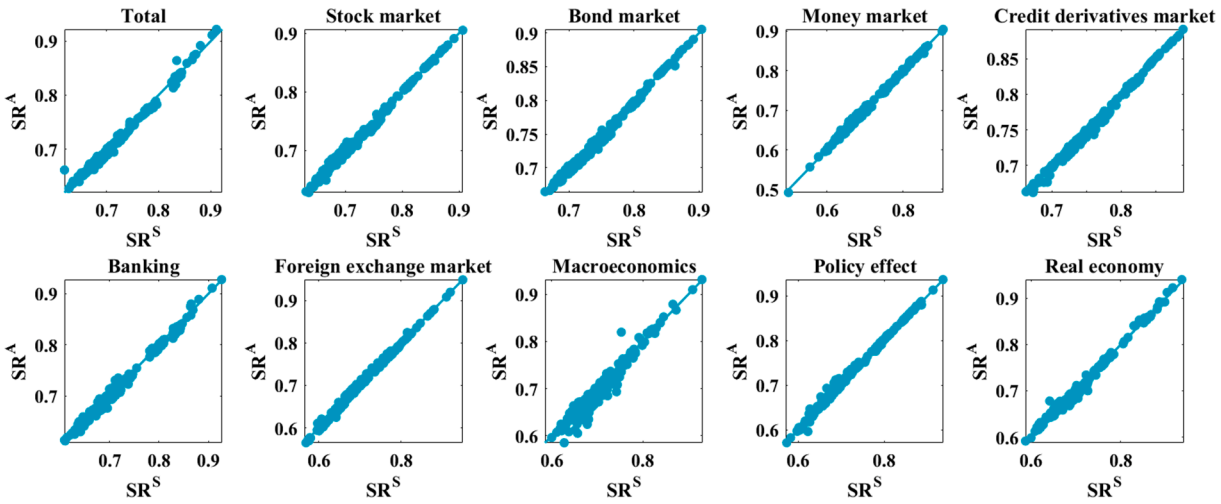

Fig. 5. Analytical solutions and simulation results for total systemic risk and systemic risk across various dimensions.

intervention, the remaining $N-1$ nodes continue to follow the dynamics described by Eq. (10), as they respond to the i forcing.

Fig. 6 illustrates the dynamic evolution of the impact of controlling each node on the total systemic risk, where the value of total systemic risk is represented by a color map. It is evident that the nodes that exhibit significantly stronger risk influence vary across different crisis stages. For example, during the subprime mortgage crisis period, nodes $X_1, X_2, X_4, X_6, X_7, X_{11}$ and X_{12} exhibited relatively better control of total systemic risk, whereas during the COVID-19 pandemic period, nodes X_1, X_2, X_4 and X_6 were relatively more effective. According to Eq. (13), the total systemic risk is determined by the systemic risk of individual nodes and their outward risk transmission. Therefore, reducing the risk of nodes with high contagion and systemic risk is relatively more effective for controlling the total systemic risk.

To further illustrate this point, we present the risk spillover of each node to other nodes and the systemic risk of each node during the entire sample period in Fig. 7. In this figure, the horizontal axis represents each node, and the vertical axis represents time. The results show that different nodes exhibit distinct characteristics during different periods. For example, during the subprime mortgage crisis, $X_1, X_2, X_3, X_4, X_6, X_7, X_{11}, X_{12}$ and X_{13} showed strong risk contagion, whereas $X_1, X_2, X_3, X_4, X_6, X_7$ and X_{14} had notably higher systemic risk. During the COVID-19 pandemic period, X_1, X_2, X_3, X_4 and X_6 presented

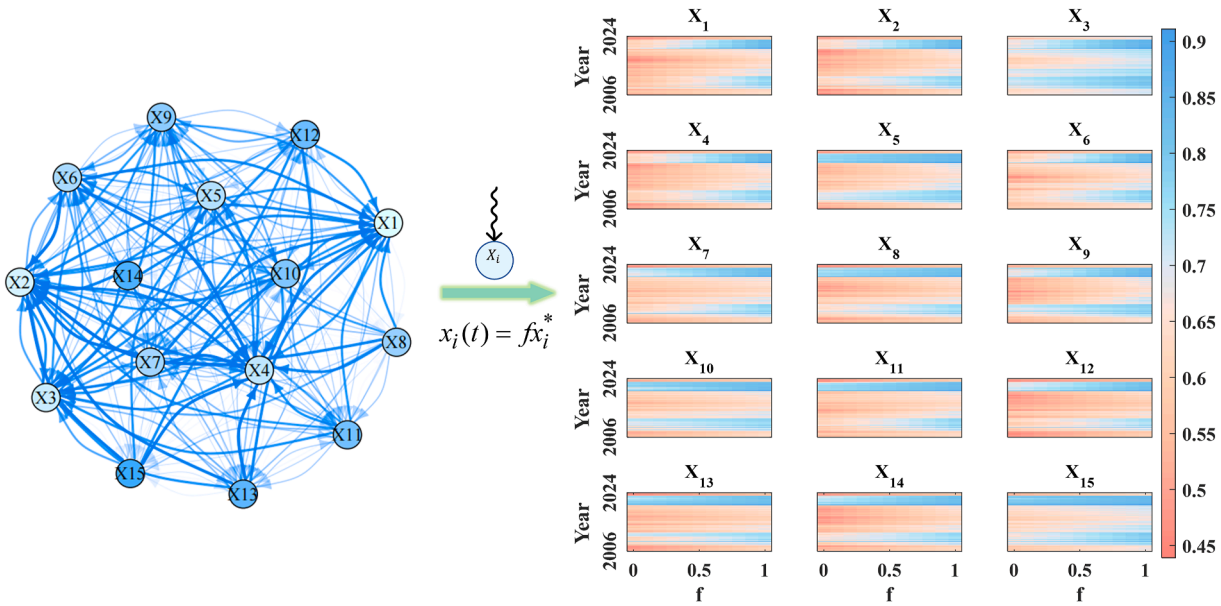

Fig. 6. Dynamic changes of the impact of node control on total systemic risk.

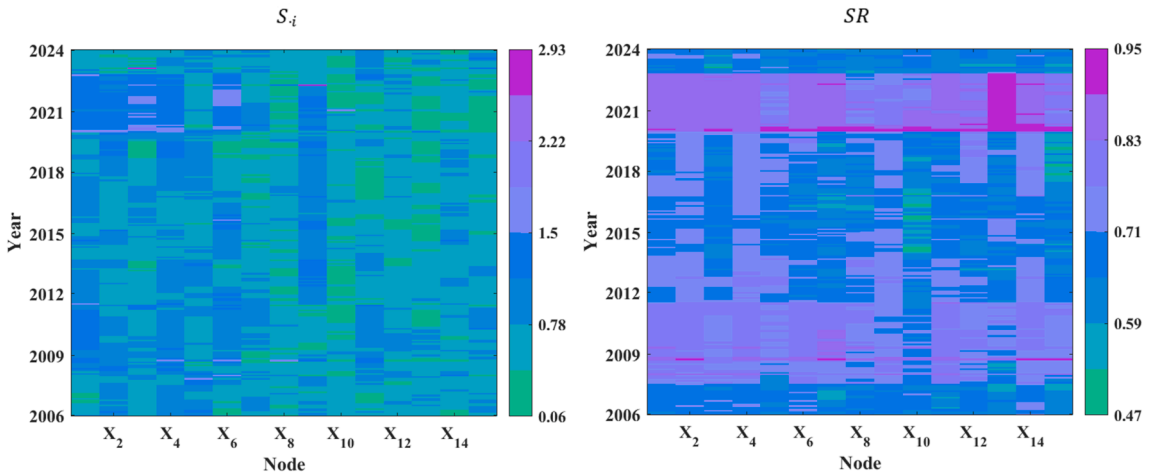

Fig. 7. The dynamic evolution of the spillover from each node to other nodes ($S_{\cdot i}$) and the systemic risk (SR) of each node.

relatively high risk contagion, whereas $X_1, X_2, X_3, X_4, X_6, X_7$ and X_{13} presented significantly greater systemic risk than did the other nodes. These results indicate that during the subprime mortgage crisis and the COVID-19 pandemic, the nodes that significantly influenced systemic risk were those with strong contagion, or those with high systemic risk, or both. This further indicates that total systemic risk is the result of the combined effects of individual node systemic risk and contagion. Owing to variations in risk contagion and systemic risk during different periods, the nodes that exhibit significantly stronger risk influence differ across crisis stages.

Given the diverse control abilities of different nodes over systemic risk, it is crucial to identify the nodes with a significant impact on the total systemic risk. In this study, we compare the effectiveness of various influence ranking algorithms listed in Section 3.2.4 based on actual risk contagion simulation results and the net spillover. The change in total systemic risk caused by forcing node i to follow $x_i(t) = fx_i^*$ represents the actual influence of the node. Since the impact of the intervened node on its neighbouring nodes is linear, the results of using the influence algorithm to identify nodes with significant influence are independent of the value of f. Therefore, we set $f = 0.9$ and evaluate the effectiveness and accuracy of these algorithms in identifying nodes with a significant impact on total systemic risk.

Fig. 8 shows the correlation between the actual influence of nodes and the results from various influence ranking algorithms. The correlations for CC_{out}, HC, GIN, and LAGC were all greater than 0.9, whereas the correlations for the other ranking algorithms were less than 0.9, suggesting that CC_{out}, HC, GIN, and LAGC outperform the other algorithms in predicting node influence. However, the consistency between the actual influence of each node and the results obtained by various influence ranking algorithms cannot be accurately determined solely from the trend of the correlation distribution in the scatter plot. Therefore, we also calculate the Kendall coefficient between the true influence ranking of each node and the rankings obtained by each influence ranking algorithm, as depicted in Fig. 8.

Fig. 9 shows that the values of the Kendall coefficient for CC_{out}, HC, GIN, and LAGC consistently reached relatively high values throughout the sample period, whereas the other algorithms exhibited significant fluctuations. Additionally, both HC and GIN maintained values above 0.6, indicating higher accuracy and stability in influence ranking. The value of the Kendall coefficient focuses on the overall sorting accuracy; however, the number of highly influential nodes relative to the total number of nodes is very small. We need to identify the nodes that significantly impact total systemic risk, thereby controlling the total systemic risk more effectively. Therefore, we compare the nodes that are in the top 30 % of the rankings by calculating the imprecision function, as shown in Fig. 9.

Fig. 10 shows that the values of the imprecision function for CC_{out}, HC, LC, GIN, and LAGC were consistently low throughout the sample period, with the values for HC and GIN remaining below 0.05. This indicates that the HC and GIN algorithms exhibit high accuracy and stability in identifying the most influential nodes. In the HITs algorithm, AC quantifies the authority of the node, reflecting its ability to receive influence, whereas HC measures the ability of the node as a central "hub" connecting other nodes, reflecting its ability to propagate influence outwards. Moreover, the GIN algorithm considers both self-importance and global importance, and compared with the LGC algorithm, which also takes into account both local and global perspectives, this algorithm introduces the natural logarithm e and uses the number of nodes n in the network as the equilibrium coefficient to avoid overestimating self-importance. These properties suggest that HC and GIN are particularly suitable for risk management.

Considering the results of the evaluation metrics discussed above, we conclude that HC and GIN perform well in identifying the nodes with the greatest impact on total systemic risk within a risk spillover network. Therefore, the HC and GIN algorithms have significant potential applications in systemic financial regulation and risk management. The high accuracy and stability of these metrics increase their reliability in identifying and monitoring key nodes within financial

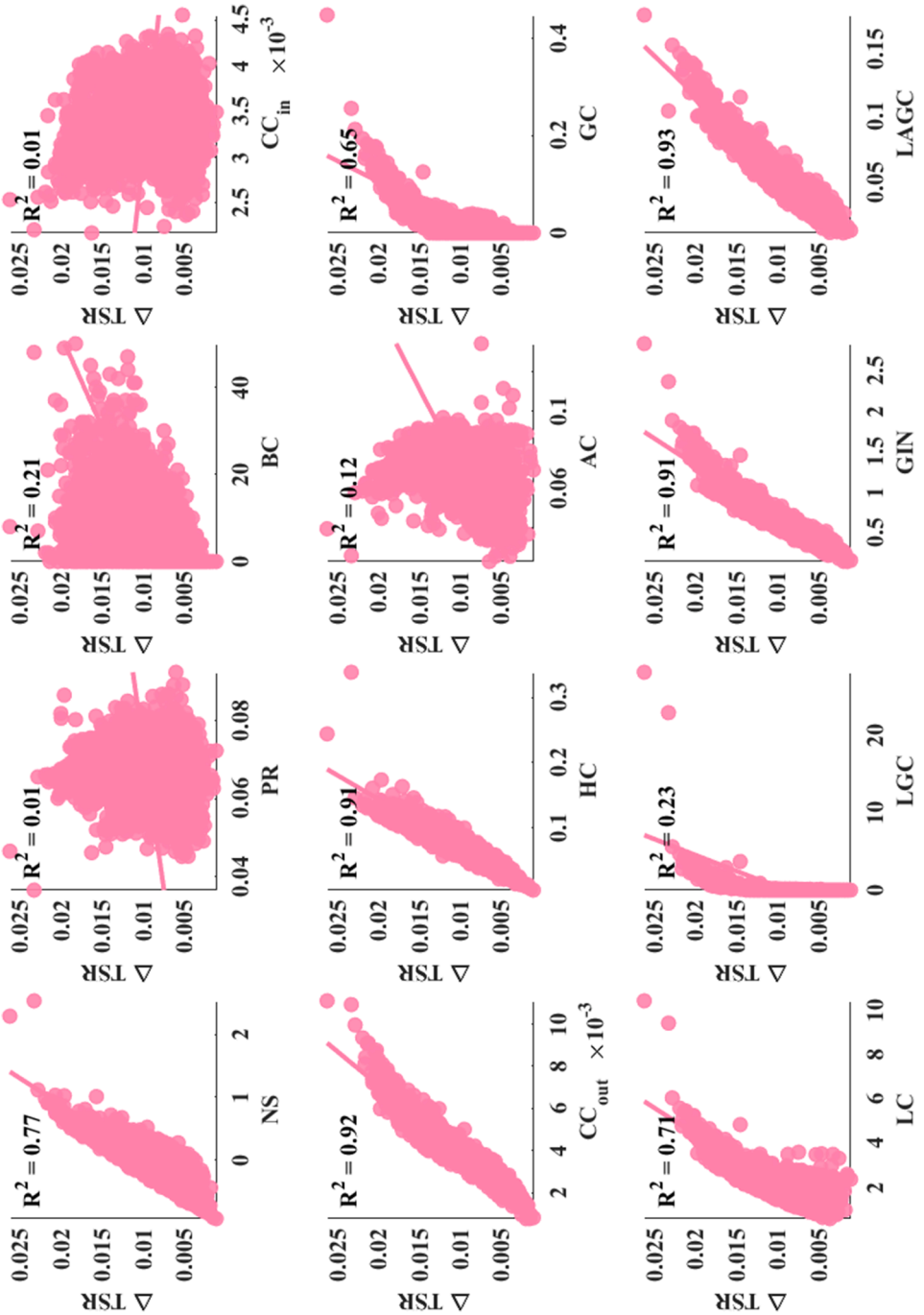

Fig. 8. Correlations between the results of various influence ranking algorithms and the actual influence.

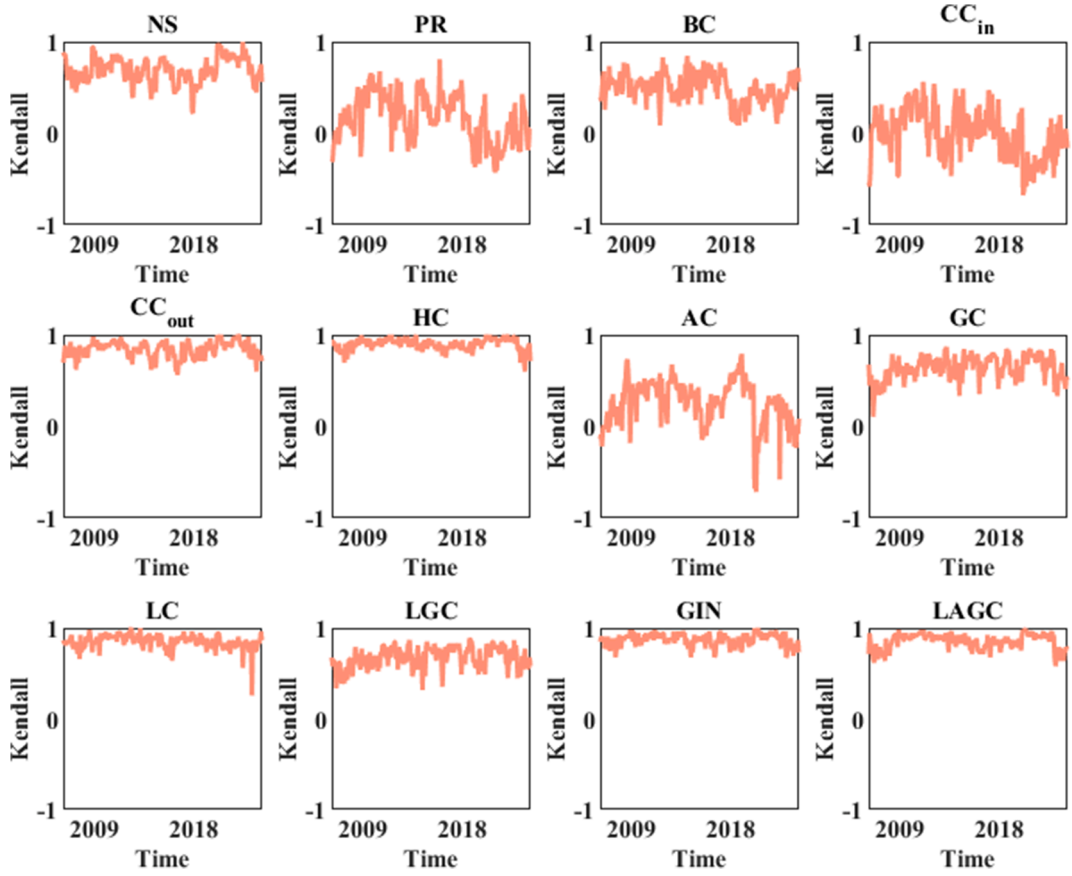

Fig. 9. Values of the Kendall coefficient between the results of various influence ranking algorithms and the actual influence.

networks. They provide valuable guidance for risk management and offer a scientific basis for maintaining financial system stability.

4.3. Sensitivity analysis

In practice, the ability of nodes to resist risk (B) and transmit risk (R) varies constantly, which in turn affects the systemic risk. Therefore, we perform dynamic perturbations to study how B and R affect systemic risk, as illustrated in Fig. 11.

Fig. 11 shows that when the ability of nodes to resist risk is low, the total systemic risk increases sharply with increasing ability of nodes to transmit risk. However, as the ability of nodes to resist risk increases, the sensitivity of the total systemic risk to the nodes' risk transmission ability significantly decreases. Therefore, enhancing the risk resistance of nodes is crucial. With higher risk resistance, the level of systemic risk remains relatively stable and is less likely to fluctuate significantly due to the risk transmission from individual nodes. Enhancing the resistance of nodes can significantly improve the stability and resilience of the financial system.

5. Conclusion and policy implications

This paper combines an econometric model, complex network, and dimensionality reduction method to accurately measure the total systemic risk and the systemic risk of each dimension in the U.S. financial system from the perspective of dynamic simulation, which provides a new framework for the measurement of systemic financial risk. To validate the performance of our method, we apply it to the U.S. financial system and compare the total risk spillover obtained via the Diebold and Yilmaz model with the total risk contagion obtained via our framework. Additionally, we compared the analytical solutions and simulation solutions of systemic risk. The results show that both sets of results are quite consistent; moreover, systemic risk accurately depicts the situation of the U.S. financial system. We empirically demonstrate that the method proposed in this paper effectively measures systemic financial risk. Specifically, compared with the DY spillover method, the cascading contamination effect of risks is considered by our method to calculate systemic risk on the basis of analysis of risk spillovers. Compared with other dynamic methods that consider risk contagion, most of these methods are

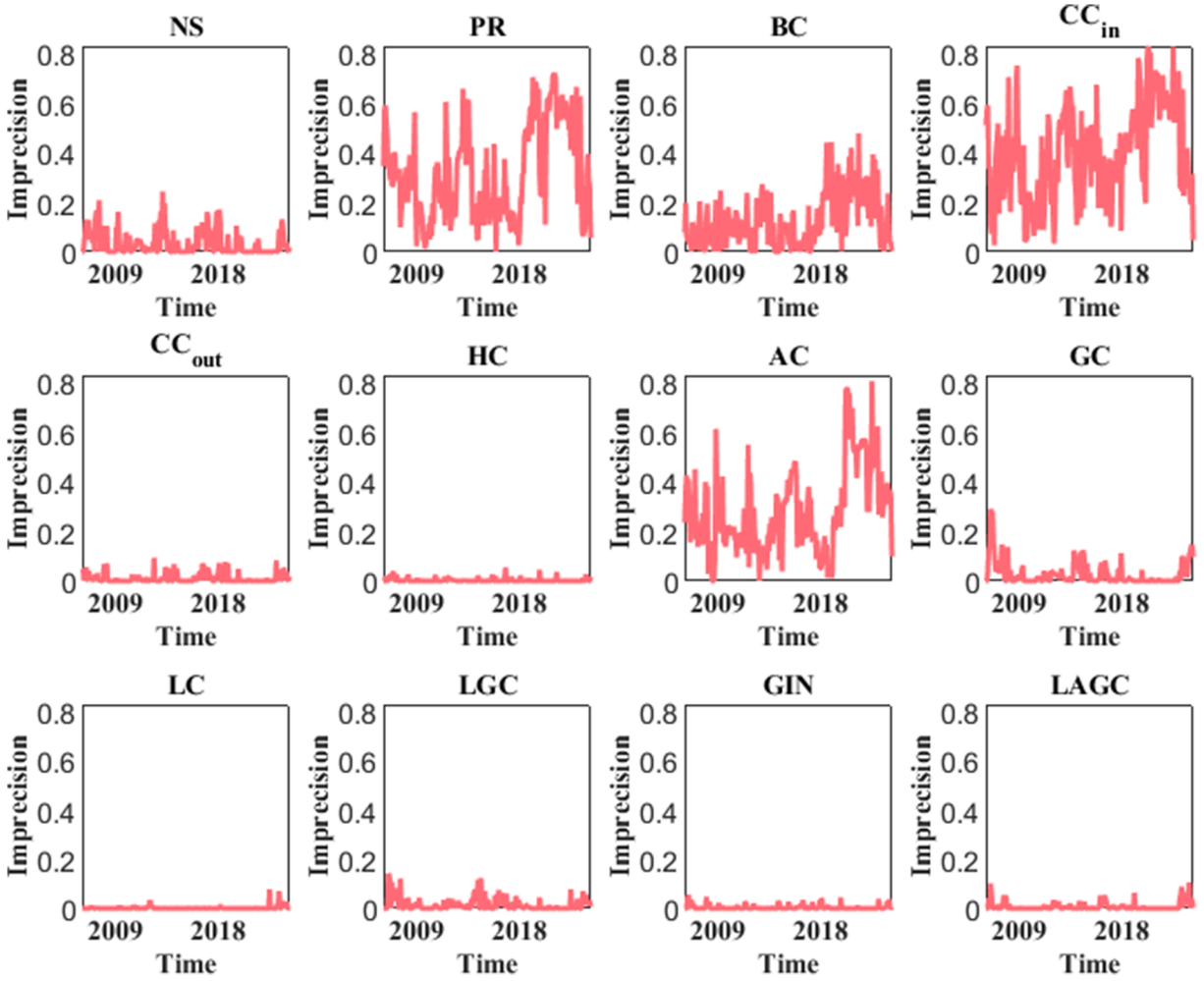

Fig. 10. Values of the imprecision functions of various influence ranking algorithms.

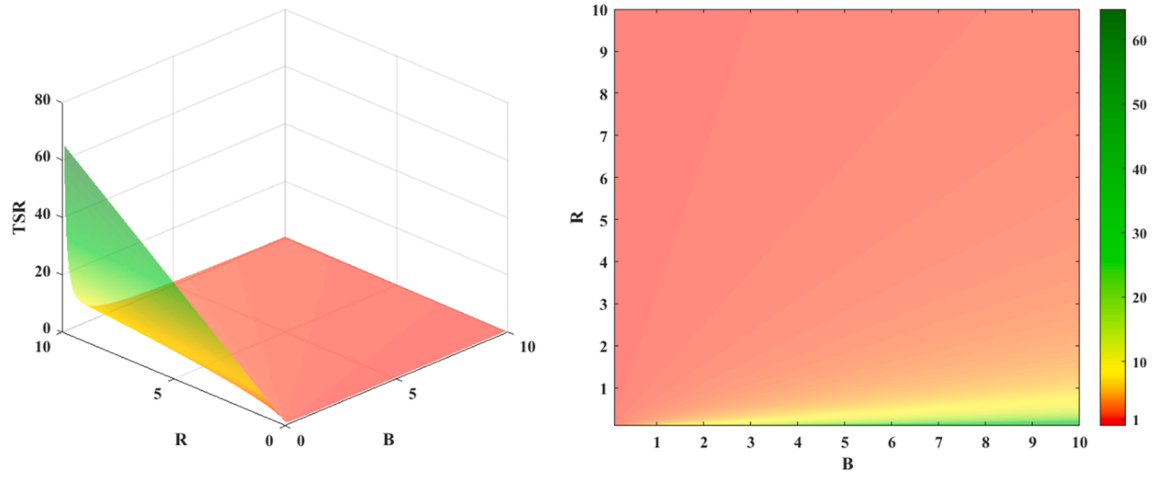

Fig. 11. Influence of B and R on total systemic risk.

aimed at discrete processes. However, our method is based on the continuous contagion of risk, which is more in line with reality. Moreover, our method can further measure the magnitude of systemic risk based on the cascading effects, rather than just reflecting whether a node is affected by other markets. In addition, this paper combines network dynamics and network dimensionality reduction methods, measuring not only the total systemic risk but also the systemic risk across various dimensions.

We studied systemic risk across all dimensions of the U.S. financial system. Based on risk measurements of risk contagion under intervention and real simulation results, we evaluated the effectiveness of various impact ranking algorithms in identifying nodes that significantly affect total systemic risk. Finally, we investigate the relationship between the ability of nodes to resist and transmit risk and the total systemic risk. Our main findings are summarized as follows. First, performance across dimensions during the COVID-19 pandemic and the subprime mortgage crisis exhibited distinct characteristics. Overall, the systemic risk level during the COVID-19 pandemic was generally higher than that during the subprime mortgage crisis, indicating that the COVID-19 pandemic had a greater impact on the US financial system. Second, among the algorithms evaluated, HC and GIN perform better and more consistently in identifying the nodes with the greatest impact on total systemic risk. This suggests that risk managers can rely on these algorithms to guide their risk management efforts more effectively. Third, the ability of the nodes to transmit risk has a significant effect on total systemic risk when the nodes have lower risk resistance, whereas this effect is smaller when the nodes have higher risk resistance. Therefore, the greater ability of nodes to resist risk enhances the resilience of the financial system.

This study has significant policy implications for preventing financial crises and promoting the stable and healthy development of the financial system. First, the framework proposed in this paper provides a quantitative tool for real-time monitoring of systemic financial risk, enabling financial regulators to assess the level of systemic risk accurately and promptly, identify potential vulnerabilities, and implement measures to reduce the likelihood of crises. Second, the framework also provides the spillover effects within the financial system, which can help financial regulators understand the direction and level of risk contagion within the financial system in a timely manner and conduct targeted regulation to effectively guide and reduce the spillover effects, lowering the degree of risk spreading throughout the entire system. Third, the framework provides risk managers with theoretical tools, namely, the influence algorithms HC and GIN, to identify key nodes that impact total systemic risk. Consequently, risk managers can prioritize their risk control efforts on those nodes that have a significant impact on total systemic risk, thereby improving the effectiveness of risk management and maintaining the stability and healthy development of the financial system. Fourth, by strengthening the ability of nodes to resist risk, policymakers can effectively curb the spread of local risks, thereby maintaining the normal operation of the financial system under pressure and preventing the emergence of financial crises.

CRediT authorship contribution statement

Yujiao Qiu: Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Xiaolei Sun:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Xiong Xiong:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Shubin Si:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Ethics statements

Not applicable because this work does not involve the use of animal or human subjects.

Declaration of competing interest

We have no potential competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (72171193; 72231008) and the Shaanxi Provincial Innovation Capacity Support Program-Science and Technology Innovation Teams (2024RS-CXTD-28).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jmse.2025.05.002.

References

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *Am. Econ. Rev., 105*(2), 564–608.
Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. *Rev. Financ. Stud., 30*(1), 2–47.
Allen, F., & Gale, D. (2000). Financial contagion. *J. Polit. Econ., 108*(1), 1–33.
Anglin, A. H., McKenny, A. F., & Short, J. C. (2018). The impact of collective optimism on new venture creation and growth: a social contagion perspective. *Entrep. Theory Pract., 42*(3), 390–425.

Babar, S., Latief, R., Ashraf, S., & Nawaz, S. (2019). Financial stability index for the financial sector of Pakistan. *Economies (Basel), 7*(3), 81.
Bao, J., Pan, J., & Wang, J. (2011). The illiquidity of corporate bonds. *J. Financ. (N. Y.), 66*(3), 911–946.
Bardoscia, M., Barucca, P., Battiston, S., Caccioli, F., Cimini, G., Garlaschelli, D., et al. (2021). The physics of financial networks. *Nat. Rev. Phys., 3*(7), 490–507.
Barzel, B., & Barabási, A. L. (2013). Universality in network dynamics. *Nat. Phys., 9*(10), 673–681.
Battaglia, F., & Gallo, A. (2013). Securitization and systemic risk: an empirical investigation on Italian banks over the financial crisis. *Int. Rev. Financ. Anal., 30*, 274–286.
Battiston, S., Farmer, J. D., Flache, A., Garlaschelli, D., Haldane, A. G., Heesterbeek, H., Hommes, C., Jaeger, C., May, R., & Scheffer, M. (2016). Complexity theory and financial regulation. *Science, 351*(6275), 818–819.
Benoit, S., Colliard, J. E., Hurlin, C., & Pérignon, C. (2017). Where the risks lie: a survey on systemic risk. *Rev. Finance, 21*(1), 109–152.
Billio, M., & Pelizzon, L. (2003). Contagion and interdependence in stock markets: have they been misdiagnosed? *J. Econ. Bus., 55*(5–6), 405–426.
Brownlees, C., & Engle, R. F. (2017). SRISK: a conditional capital shortfall measure of systemic risk. *Rev. Financ. Stud., 30*(1), 48–79.
Bucci, A., La Torre, D., Liuzzi, D., & Marsiglio, S. (2019). Financial contagion and economic development: An epidemiological approach. *J. Econ. Behav. Organ. , 162*, 211–228.
Cabrales, A., Gottardi, P., & Vega-Redondo, F. (2017). Risk sharing and contagion in networks. *Rev. Financ. Stud., 30*(9), 3086–3127.
Caramazza, F., Ricci, L., & Salgado, R. (2000). Trade and financial contagion in currency crises. *IMF Working Paper, 55*, 1–47.
Cardarelli, R., Elekdag, S., & Lall, S. (2011). Financial stress and economic contractions. *J. Financ. Stabil., 7*(2), 78–97.
Chadwick, M. G. (2019). Dependence of the “Fragile Five” and “Troubled Ten” emerging market financial systems on US monetary policy and monetary policy uncertainty. *Res. Int. Bus. Finance, 49*, 251–268.
Chen, J., & Zhang, J. (2023). Crude oil price shocks, volatility spillovers, and global systemic financial risk transmission mechanisms: evidence from the stock and foreign exchange markets. *Resour. Policy, 85*, Article 103875.
Chowdhury, P., Paul, S. K., Kaisar, S., & Moktadir, M. A. (2021). COVID-19 pandemic related supply chain studies: a systematic review. *Transport. Res. E Logist. Transport. Rev., 148*, Article 102271.
Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: predictive directional measurement of volatility spillovers. *Int. J. Forecast., 28*(1), 57–66.
Dodds, P. S., & Watts, D. J. (2005). A generalized model of social and biological contagion. *J. Theor. Biol., 232*(4), 587–604.
Duan, D., Wu, C., Zhai, Y., Lv, C., & Wang, N. (2022). Coexistence mechanism of alien species and local ecosystem based on network dimensionality reduction method. *Chaos Solitons Fractals, 159*, Article 112077.
Elliott, M., Golub, B., & Jackson, M. O. (2014). Financial networks and contagion. *Am. Econ. Rev., 104*(10), 3115–3153.
Engle, R. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J. Bus. Econ. Stat., 20*(3), 339–350.
Erik, B., Lombardi, M., Mihaljek, D., Shin, H.S., 2019. Financial conditions and purchasing managers’ indices: exploring the links. BIS Q. Rev. Sept. 2019, 65-79. https://www.bis.org/publ/qtrpdf/r_qt1909g.htm.
Estrella, A., & Hardouvelis, G. A. (1991). The term structure as a predictor of real economic activity. *J. Financ. (N. Y.), 46*(2), 555–576.
Estrella, A., & Mishkin, F. S. (1998). Predicting US recessions: financial variables as leading indicators. *Rev. Econ. Stat., 80*(1), 45–61.
Farmer, J. D., & Foley, D. (2009). The economy needs agent-based modelling. *Nature, 460*(7256), 685–686.
Frankel, J. A., & Rose, A. K. (1996). Currency crashes in emerging markets: an empirical treatment. *J. Int. Econ., 41*(3–4), 351–366.
Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Soc. Netw., 1*, 215–239.
Gao, J., Barzel, B., & Barabási, A. L. (2016). Universal resilience patterns in complex networks. *Nature, 530*(7590), 307–312.
Garas, A., Argyrakis, P., Rozenblat, C., Tomassini, M., & Havlin, S. (2010). Worldwide spreading of economic crisis. *New J. Phys., 12*(11), 113043.
Gleich, D. F. (2015). PageRank beyond the web. *SIAM Rev., 57*(3), 321–363.
Gong, X. L., Feng, Y. K., Liu, J. M., & Xiong, X. (2023a). Study on international energy market and geopolitical risk contagion based on complex network. *Resour. Policy, 82*, Article 103495.
Gong, X. L., Zhao, M., Wu, Z. C., Jia, K. W., & Xiong, X. (2023b). Research on tail risk contagion in international energy markets—the quantile time-frequency volatility spillover perspective. *Energy Econ., 121*, Article 106678.
Haas, A., Laubichler, M., Applegate, J., Steudle, G., & Jaeger, C. C. (2022). A proposal for integrating theories of complexity for better understanding global systemic risks. *Risk Anal., 42*(9), 1945–1951.
Hakkio, C. S., & Keeton, W. R. (2009). Financial stress: what is it, how can it be measured, and why does it matter. *Econ. Rev., 94*(2), 5–50.
Hao, J., Li, J. P., Feng, Q. Q., & Sun, X. L. (2023). Early warning of financial crisis based on the spillover effects. *Chin. J. Manag. Sci., 31*(4), 35–45 (In Chinese).
Horta, P., Mendes, C., & Vieira, I. (2010). Contagion effects of the subprime crisis in the European NYSE Euronext markets. *Port. Econ. J., 9*, 115–140.
Hou, G., Chen, Y., Liu, X., Zhang, D., Geng, Z., & Si, S. (2024). A resilience approach for diagnosing and predicting HBV-related diseases based on blood tests. *Engineering, 32*, 174–185.
Hsueh, L. P., & Chandy, P. R. (1989). An examination of the yield spread between insured and uninsured debt. *Financ. Rev. (Buffalo, N. Y.), 12*(3), 235–244.
Illing, M., & Liu, Y. (2006). Measuring financial stress in a developed country: an application to Canada. *J. Financ. Stabil., 2*(3), 243–265.
Ishrakieh, L. M., Dagher, L., & El Hariri, S. (2020). A financial stress index for a highly dollarized developing country: the case of Lebanon. *Central Bank Rev., 20*(2), 43–52.
Kaminsky, G., Lizondo, S., & Reinhart, C. M. (1998). Leading indicators of currency crises. *IMF Staff Pap., 45*(1), 1–48.
Karlebach, G., & Shamir, R. (2008). Modelling and analysis of gene regulatory networks. *Nat. Rev. Mol. Cell Biol., 9*(10), 770–780.
Kaufman, G. G. (2000). Banking and currency crises and systemic risk: lessons from recent events. *Econ. Perspect., 24*(3), 9–28.
Kendall, M. G. (1938). A new measure of rank correlation. *Biometrika, 30*(1–2), 81–93.
Kitsak, M., Gallos, L. K., Havlin, S., Liljeros, F., Muchnik, L., Stanley, H. E., & Makse, H. A. (2010). Identification of influential spreaders in complex networks. *Nat. Phys., 6*(11), 888–893.
Leontief, W. (1974). Structure of the world economy: outline of a simple input-output formulation. *Am. Econ. Rev., 64*(6), 823–834.
Li, S., & Wang, C. (2021). Network structure, portfolio diversification and systemic risk. *J. Manag. Sci. Eng., 6*(2), 235–245.
Louis, R.J., Balli, F., 2013. Low-inflation-targeting monetary policy and differential unemployment rate: Is monetary policy to be blamed for the financial crisis?—Evidence from major OECD countries. Econ. Model. 30, 546-564. https://doi.org/10.1016/j.econmod.2012.09.042.
Lucas, K., Renn, O., & Jaeger, C. (2018). Systemic risks: theory and mathematical modeling. Adv. *Theory Simul., 1*(11), Article 1800051.
Ma, L. L., Ma, C., Zhang, H. F., & Wang, B. H. (2016). Identifying influential spreaders in complex networks based on gravity formula. *Physica A, 451*, 205–212.
Ma, M., Bao, T., & Wen, Y. (2023). Enhancing portfolio performance with crypto tokens: a correlation network analysis. In *2023 IEEE 43rd International Conference on Distributed Computing Systems Workshops (ICDCSW)* (pp. 31–36).
Meng, X., Fan, Y., Qiao, Y., Lin, J., Cai, Z., & Si, S. (2025). Evolutionary analysis of a coupled epidemic-voluntary vaccination behavior model with immunity waning on complex networks. *Risk Anal.*. https://doi.org/10.1111/risa.17699, 1–20.
Merton, R. C. (1977). An analytic derivation of the cost of deposit insurance and loan guarantees an application of modern option pricing theory. *J. Bank. Finance, 1*(1), 3–11.
Newman, M. E. (2005). A measure of betweenness centrality based on random walks. *Soc. Netw., 27*(1), 39–54.
Novozhilov, A. S., Karev, G. P., & Koonin, E. V. (2006). Biological applications of the theory of birth-and-death processes. *Briefings Bioinf., 7*(1), 70–85.
O’Brien, J., & Szerszeń, P. J. (2017). An evaluation of bank measures for market risk before, during and after the financial crisis. *J. Bank. Finance., 80*, 215–234.
Ouyang, R., Chen, X., Fang, Y., & Zhao, Y. (2022). Systemic risk of commodity markets: a dynamic factor copula approach. *Int. Rev. Financ. Anal., 82*, Article 102204.
Page, L., Brin, S., Motwani, R., & Winograd, T. (1999). *The PageRank Citation Ranking: Bringing Order to the Web*. Stanford infolab.

Qi, X., Duval, R. D., Christensen, K., Fuller, E., Spahiu, A., Wu, Q., et al. (2013). Terrorist networks, network energy and node removal: a new measure of centrality based on Laplacian energy. *Soc. Netw., 2*(1), 19–31.
Ross, S. A. (1989). Information and volatility: the no-arbitrage martingale approach to timing and resolution irrelevancy. *J. Financ. (N. Y.), 44*(1), 1–17.
Sachs, J. D., Tornell, A., & Velasco, A. (1996). Financial crises in emerging markets: the lessons from 1995. *Brookings Pap. Econ. Activ., 27*(1), 147–199.
Sanhedrai, H., Gao, J., Bashan, A., Schwartz, M., Havlin, S., & Barzel, B. (2022). Reviving a failed network through microscopic interventions. *Nat. Phys., 18*(3), 338–349.
Schweitzer, F., Fagiolo, G., Sornette, D., Vega-Redondo, F., Vespignani, A., & White, D. R. (2009). Economic networks: the new challenges. *Science, 325*(5939), 422–425.
Sedunov, J. (2016). What is the systemic risk exposure of financial institutions? *J. Financ. Stabil., 24*, 71–87.
Si, S., Lv, C., Cai, Z., Duan, D., Kurths, J., & Wang, Z. (2023). Fractional core-based collapse mechanism and structural optimization in complex systems. *Sci. China Inf. Sci., 66*(9), 1–16.
Sun, X., Wang, J., Yao, Y., Li, J., & Li, J. (2020). Spillovers among sovereign CDS, stock and commodity markets: a correlation network perspective. *Int. Rev. Financ. Anal., 68*, Article 101271.
Tobias, A., & Brunnermeier, M. K. (2016). CoVaR. *Am. Econ. Rev., 106*(7), 1705.
Traulsen, A., Nowak, M. A., & Pacheco, J. M. (2006). Stochastic dynamics of invasion and fixation. *Phys. Rev. E, 74*(1), Article 011909.
Uhde, A., & Heimeshoff, U. (2009). Consolidation in banking and financial stability in Europe: empirical evidence. *J. Bank. Finance, 33*(7), 1299–1311.
Ullah, A., Wang, B., Sheng, J., Long, J., Khan, N., & Sun, Z. (2021). Identifying vital nodes from local and global perspectives in complex networks. *Expert Syst. Appl., 186*, Article 115778.
Wang, G. J., Feng, Y., Xiao, Y., Zhu, Y., & Xie, C. (2022). Connectedness and systemic risk of the banking industry along the Belt and Road. *J. Manag. Sci. Eng., 7*(2), 303–329.
Wang, G. J., Huai, H., Zhu, Y., Xie, C., & Uddin, G. S. (2024). Portfolio optimization based on network centralities: which centrality is better for asset selection during global crises? *J. Manag. Sci. Eng., 9*(3), 348–375.
Wang, Z., Gao, X., Huang, S., Sun, Q., Chen, Z., Tang, R., & Di, Z. (2022). Measuring systemic risk contribution of global stock markets: a dynamic tail risk network approach. *Int. Rev. Financ. Anal., 84*, Article 102361.
Welburn, J. W., & Strong, A. M. (2022). Systemic cyber risk and aggregate impacts. *Risk Anal., 42*(8), 1606–1622.
Xu, Q., Li, M., Jiang, C., & He, Y. (2019). Interconnectedness and systemic risk network of Chinese financial institutions: a LASSO-CoVaR approach. *Physica A, 534*, Article 122173.
Zhang, Q., Shuai, B., & Lü, M. (2022). A novel method to identify influential nodes in complex networks based on gravity centrality. *Inf. Sci., 618*, 98–117.
Zhao, J., Wang, Y., & Deng, Y. (2020). Identifying influential nodes in complex networks from global perspective. *Chaos Solitons Fractals, 133*, Article 109637.